

An Indoor Mobile Robot 2D Lidar Mapping Based on Cartographer-Slam Algorithm

Jie Yu¹, Ao Zhang², Yong Zhong^{2*},

¹Shool of Mechanical and Automotive Engineering,
Fujian University of Technology, Fuzhou 350118, China
²Fujian Key Laboratory of Automotive Electronics and Electric Drive
(Fujian University of Technology), Fuzhou 350118, China
95677615@qq.com, 1174796303@qq.com, 345105193@qq.com

Trong-The Nguyen^{3,4*}, Trinh-Dong Nguyen^{3,4}

³ University of Information Technology, Ho Chi Minh City 700000, Vietnam

⁴Vietnam National University, Ho Chi Minh City 700000, Vietnam;
thent@uit.edu.vn, dongnt@uit.edu.vn

*Corresponding authors: Yong Zhong, Trong-The Nguyen

Received May 24, 2022, revised June 20, 2022, accepted July 26, 2022.

ABSTRACT. *Mapping an unfamiliar environment is one of the essential tasks in success prerequisite for accurate navigation of mobile robots. This study suggests an indoor machine 2D Lidar mapping based on the cartographer algorithm using synchronous localization and mapping (SLAM) for mobile robot navigation. In the experimental section, two scenarios: in simulation and systems in actual experiments are carried out to evaluate the suggested approach. A built crawler mobile robot test is mainly equipped with Lidar A1 radar and the Jetson nano main control board with running memory for a real scenario. A robot operating system (ROS) is used to construct a simulation environment for making mainstream map implementation as in an indoor portable machine test. The obtained experimental results of the suggested approach are compared with the other schemes, such as the G-mapping and Hector approaches, from the perspectives of synchronous positioning and mapping accuracy, computational complexity, and mapping efficiency. The results show that the introduced Cartographer SLAM algorithm performs best in an unfamiliar indoor environment.*

Keywords: Indoor mobile robot mapping; Simultaneous localization and mapping (SLAM); Robot operating system (ROS); 2D lidar; Indoor mobile robot

1. **Introduction.** In an unknown indoor environment, a mobile robot uses sensor information to locate itself and construct an environment map in real-time, called synchronous localization and mapping (SLAM)[1, 2]. The mobile robot must select the appropriate SLAM algorithm to establish an accurate environment map in the unknown environment [3]. 2D lidar has the advantages of solid robustness, good economy, high accuracy, and small cumulative error [4, 5]. It stands out among many sensors and is often used as the first choice for an indoor mobile robot to construct environment maps and positions [6]. Many SLAM algorithms are developed based on 2D light detection and ranging laser (Lidar) under a robot operating system with sensor and robot technology [7]. Several popular SLAM algorithms have been proposed in the platform for robot development with a robot operating system (ROS), e.g., the G.mapping [8], and Hector [9] schemes.

ROS has been widely used in the robot industry worldwide because it is considered a robot project software platform for robot development [10].

A recently developed SLAM scheme potential method called Cartographer has been proposed based on a 2D Lidar with ROS [11]. The cartographer has advantages, e.g., high code reuse rate, simple structure, rich software kits, and free and open-source. The mapping in unfamiliar environments with appropriate algorithms is a challenging issue for success prerequisite for accurate navigation of mobile robots.

This study suggests an indoor machine 2D Lidar mapping based on the cartographer-Slam algorithm for mobile robot navigation. As in an indoor portable machine test, a simulation environment is constructed with ROS for map building in an unfamiliar indoor environment. After building the map, the main task is to evaluate the results of the suggested scheme in comparison with the other algorithms in the literature [12, 13]. In the experimental section, different slam systems are used as test scenarios based on the 2D lidar of the slam system [14], such as the slam system based on a monocular camera [15] and the slam system based on a stereo camera [16] are tested and compared on the same data set [17]. The obtained experimental results of the suggested approach are compared with the other schemes, such as the G-mapping, and Hector approaches, in the perspectives of synchronous positioning and mapping accuracy, computational complexity, and mapping efficiency [18]. The results show that the introduced Cartographer SLAM algorithm performs best in an unfamiliar indoor environment. The contributions of the paper are highlighted as follows.

- The cartographer SLAM algorithm applies to indoor machine mapping for the first time.
- The slam algorithms intuitively from the environment are reviewed with validating performance and discussion about their advantages and disadvantages.
- The iterative nearest point method, structural similarity index and Hausdorff distance are proposed to compare the maps constructed by the turtle bot3 mobile robot.

The results directly discuss efficiency and accuracy in Orb SLAM2 with rich 3D environment features on the map. The rest of the paper is organized as follows: the first section introduces the necessity of mapping an unfamiliar environment as one of the essential tasks in the success prerequisite for accurate navigation of mobile robots. The second section describes the principle of the SLAM algorithm. The slam map evaluation standard is proposed in the second section, and then the simulation and accurate experiment results are analyzed in the fourth section. The final section summarizes the research conclusions and prospects.

2. Cartographer - SLAM Algorithm. Cartographer-SLAM algorithm [11] is a recent SLAM graph optimal mapping algorithm that adapted the scene with a large area with closed-loop detection to eliminate the error and avoid faulty construction. The main goal of SLAM, based on graph optimization, is to create a real-time pose map for a mobile robot. The node represents the robot's stance, while the edge represents the transformation relationship between each node. In contrast to the SLAM, The SLAM based on graph optimization is divided into two modules based on the filtering method: the front-end and the back-end, with the back-end introducing the closed-loop detection connection. As a result, the SLAM based on graph optimization is divided into the front-end module and the back-end module, as opposed to the particle filter algorithm. The graph optimization algorithm is capable of adapting to a large-scale scenario. Closed-loop detection can detect the error and prevent improper construction caused by the accumulation of errors [11].

The cartographer framework has three main components: local mapping, closed-loop detection, and global mapping. Unlike other slam lidar algorithms, the concept of submap is introduced into the front end of the cartographer algorithm. When the front-end carries out data extraction and data association, a subgraph is formed every time the lidar scans. The data frame obtained from each scan will be compared with the previous sub-graph and inserted into the last sub-graph. The updating and optimization of the sub-graph depend on the continuous insertion of the data frame. A complete optimized sub-graph will be formed whenever no data frame is inserted. Here, the non-linear least square method is used to solve the problem. The objective function of posture optimization is modeled to effectively reduce the cumulative error in local mapping over iterations, several subgraphs, namely local maps, as follows.

$$f = \arg \min_{\xi} \sum_{k=1}^K 1 - (M_{smooth}(T_{\xi}h_k))^2 \quad (1)$$

where T_{ξ} is the relative transfer matrix; h_k is the data point in the radar frame; M_{smooth} is a bicubic interpolation function. The closed-loop detection is carried out to the existence of the accumulated position and pose error of local mapping, the map constructed by the robot has the problem of ghosting. The global constraint method is used to construct the closed-loop constraint to improve the efficiency of the whole pose detection. The bicubic interpolation function is used to determine the radar scan profile. The matching degree between and local subgraph. The cartographer uses a sparse pose map to do global optimization, and the global pose of the robot corresponding to all radar frame: $\Xi^s = \{\xi_j^s\}, j = 1, 2, \dots, n$. Global pose corresponding to all local subgraphs: $\Xi^m = \{\xi_j^m\}, j = 1, 2, \dots, n$. The mathematical expression of the global mapping is shown as follows. The mathematical expression of the global mapping is shown as follows.

$$f_{mapping} = \arg \min_{\Xi^m, \Xi^s} \frac{1}{2} \sum_{ij} \rho \left(E^2 \left(\xi_I^m, \xi_j^s, \sum_{ij} \xi_{ij} \right) \right) \quad (2)$$

where i and j are the serial number of radar scanning frame and the subgraph number, ρ is loss function that used to punish those errors that are too large. When the closed-loop is detected, all the pose values in the whole pose map are optimized globally: Ξ^s and Ξ^m . All the positions and poses in the algorithm will be modified, and the corresponding map points on each pose will be modified accordingly, which is called global mapping. The cartographer principle [11] is shown in Figure 1.

3. An Indoor Machine Mapping with Cartographer.

3.1. Space Workload Environment Setting. The described equipment and environment are presented as follows. A center controller with a notebook with i7-11800, an 8-core processor, and 16GB running memory is used for the experiment [14]. A built-in gazebo based on ROS is used as a mobile robot model simulator [19]. A built crawler mobile robot is used as the test robot that is mainly equipped with rplidar A1 radar of Silan technology, and the main control board is Jetson nano with running memory of 4GB. Figure 2 shows a crawler mobile robot with Silan technology plidar A1 radar, main control nano board, and 4GB memory [16]. The center device can connect the mobile robot through SSH command in the slave terminal, control its movement and complete the map construction on the slave machine.

The environment space is a large-scale in door house. It can be a closed warehouse for setting a large-scale environment. Figure 3 displays a closed house using the laboratory as actual mapping construction.

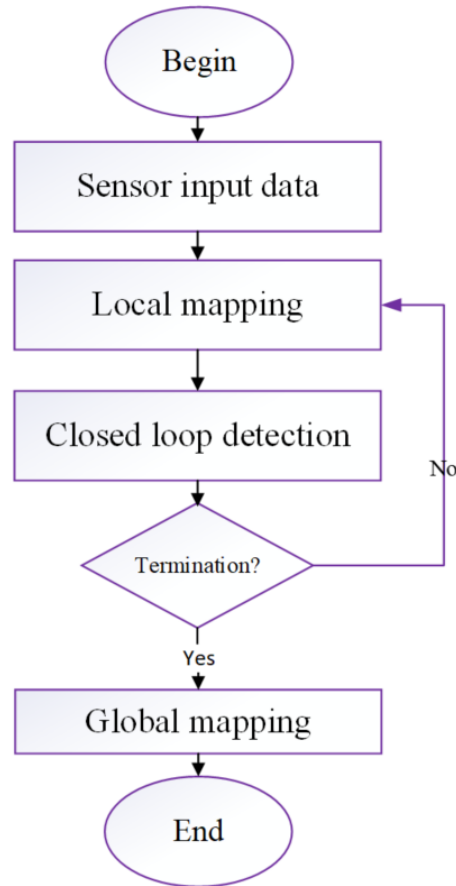


FIGURE 1. Schematic diagram of cartographer SLAM algorithm

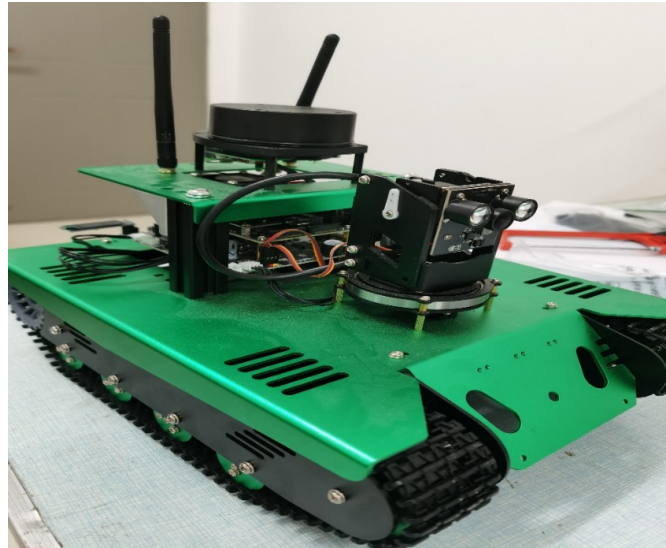


FIGURE 2. A mobile robot with Crawler

3.2. A Map Construction Process. The assumed robot is mainly equipped with rplidar A1 radar of Silan technology, and the main control board is Jetson nano with a running memory of 4GB. An unfamiliar environment is set in the map construction environment, subsequent steps of mobile robot precise navigation are set to prepare with



FIGURE 3. An example of a real closed house used in actual mapping construction

safety obstacle avoidance, and the corresponding evaluation criteria must be established. The suggested scheme is mainly implemented in the map construction process as follows.

1. The SLAM algorithm's precision has visually assessed the map for flaws, ambiguity, and jaggedness, as well as whether the features are visible. The algorithm's accuracy, the distance between essential feature points represented in the map, such as the distance between the wall and so on, can be made more intuitive.
2. The time spent building the map with the environment map, following the same route, and moving at the same speed until the finished map with closed-loop detection. The position and pose error of local mapping is implemented in complete pose detection.
3. The algorithm's complexity is represented in the CPU occupancy rate. The greater the algorithm's occupancy rate, the more complicated the algorithm is; on the other hand, the lower the algorithm's complexity.

4. **Experimental Results and Discussion.** There are two scenarios for testing the suggested scheme: scenarios in simulation and systems in actual experiments. The outcome results of the proposed approach are compared with the other methods, e.g., the G-mapping [8] and Hector [9] SLAM algorithms, to evaluate the suggested scheme's performance.

4.1. **Results with Scenarios in Simulation.** The slam algorithms are set in the same conditions in order to compare the accuracy. Several feature points are selected in the simulation environment with a built-in gazebo based on ROS. The calculated absolute value data and absolute error data of the algorithms are compared with the measured values of the algorithms. Figure 4 shows the comparison line chart of the relative error of the three algorithms. The map constructed results are of the suggested scheme smoother and more precise than the other two algorithms, with small and few sawteeth, and the contour of obstacles is relatively complete.

In the observation from Figure 4, it can be seen the advantages and disadvantages of the accuracy of the algorithms. The maximum absolute error of the suggested cartographer is 4.44% the minimum is 0%, and the variance is 0.076, while the maximum absolute

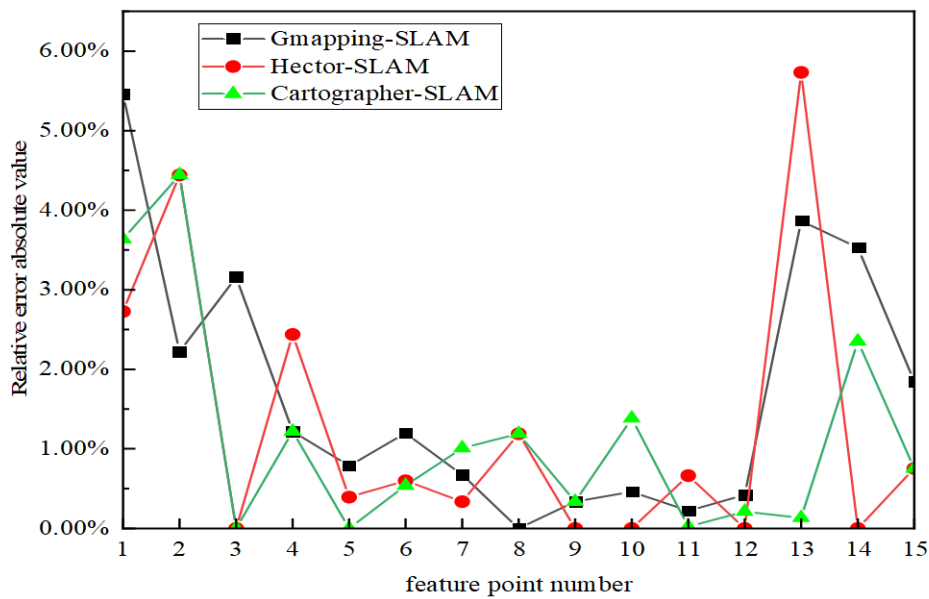


FIGURE 4. Comparison of absolute relative error values of three slam algorithms in simulation

TABLE 1. The results of the comparison of the three methods in simulation scenarios

Algorithm	Map accuracy	Map completion time (s)	Minimum CPU utilization	Maximum CPU utilization
G-mapping	3	1256	19.1%	20.4%
Hector	2	1960	18.9%	19.2%
Cartographer	1	1372	18.4%	19.8%

value of the absolute error of G-mapping is 5.5%, and the minimum value is 0%, and the variance is 0.105. The absolute error of Hector is 73.0% and the absolute error is 73.0%. Therefore, the cartographer SLAM algorithm has the best stability, the Hector SLAM algorithm takes second place, and the G-mapping SLAM algorithm [8] is relatively unstable.

Figure 5 compares the graph map constructed by the proposed cartographer scheme with the G-mapping and Hector SLAM algorithms. The three slam algorithms can build the environment map successfully. Remarkably, the outcome of the suggested scheme Cartographer SLAM algorithm is the best one with the map constructed by the whole is smoother and more straightforward than the other two algorithms, with small and few sawteeth, and the contour of obstacles is relatively complete. The resulting mapping of the Hector SLAM algorithm is better than the G-mapping SLAM algorithm. The sawtooth, the silhouette of some blocks on the walls on the map of the G-mapping scheme not recognized completely.

The mobile robot travel at the speed of 0.2m/s, completes the map construction three times along the same route, records the completion time, and takes the average value. Table 1 shows the results of the comparison of the three methods with values of ranking and timing execution. The ranking map accuracy and checking CPU utilization are two parameters to measure the performance of the methods. The G-mapping algorithm would

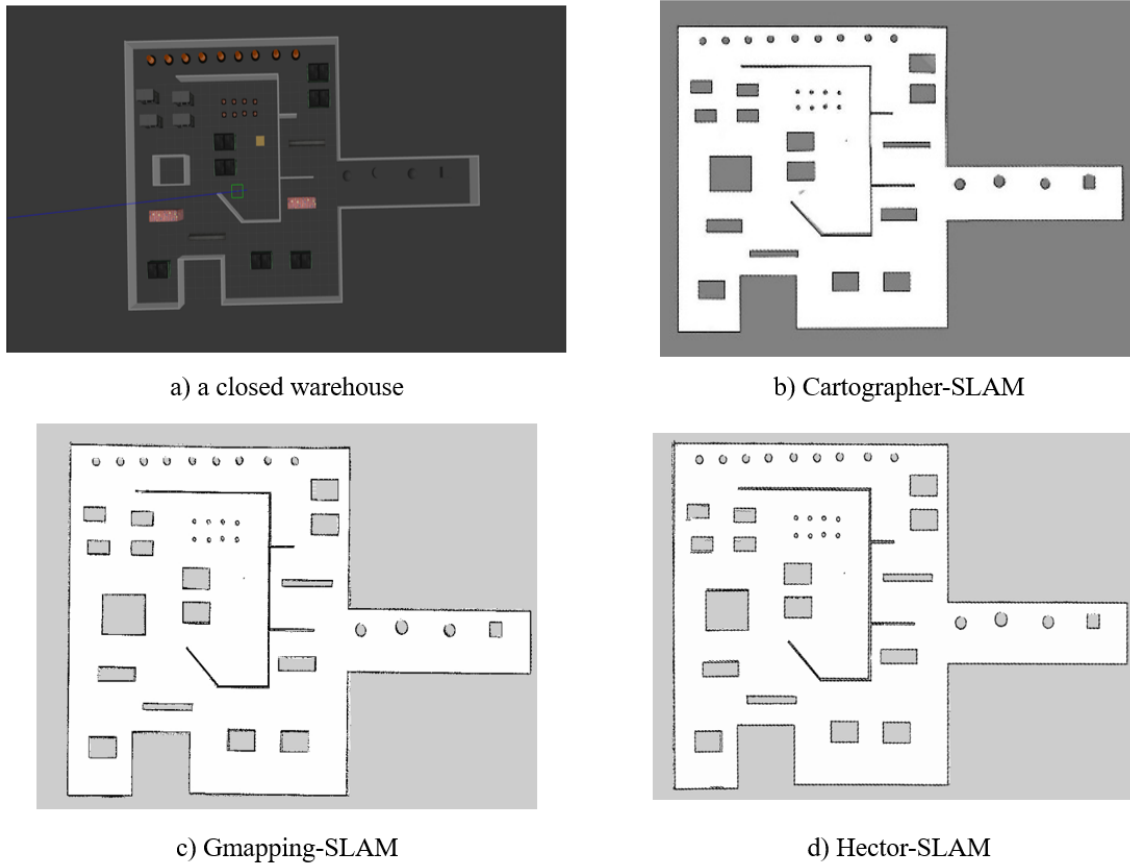


FIGURE 5. The graph map constructed by the algorithms in simulation

take 1256 seconds for map construction completed, and the CPU consumption is higher than the other two algorithms. It shows that the complexity of the algorithm is slightly higher. The construction time of the Hector SLAM algorithm, and its CPU utilization are the lowest. The completion time of the cartographer SLAM algorithm is 1672s, and the CPU utilization rate is the second.

4.2. Results Systems in Actual Experiment. A mobile robot would be taken the route and the related route is recorded with the time from the beginning of the robot to the time when the map is built. Figure 6 shows a real environment constructed mapping by the suggested algorithm with the G-mapping and Hector algorithms for path mapping. The cartographer algorithm has the best definition compared with G-mapping and Hector algorithm. There are many jagged walls on the map constructed by the Hector.

Figure 7 depicts the comparison of the measured error values of the three algorithms. The compared and analyzed map results show that the suggested scheme outperforms the algorithms. The corresponding values of feature points in the constructed map are measured with walls, columns, and stations with noticeable features for testing the accuracy performance.

The line chart of absolute value comparison of relative errors shows the relative error of the cartographer SLAM algorithm is far less than that of the other two algorithms. The maximum absolute value of the relative error of the cartographer SLAM algorithm is 6.52%, the minimum is 0.000%, and the variance between the measured value of the feature point map and the actual error is 0.0004. The maximum absolute error of Hector slam is 14%, the minimum is 0.15%, and the variance is 0.0015. The maximum total value

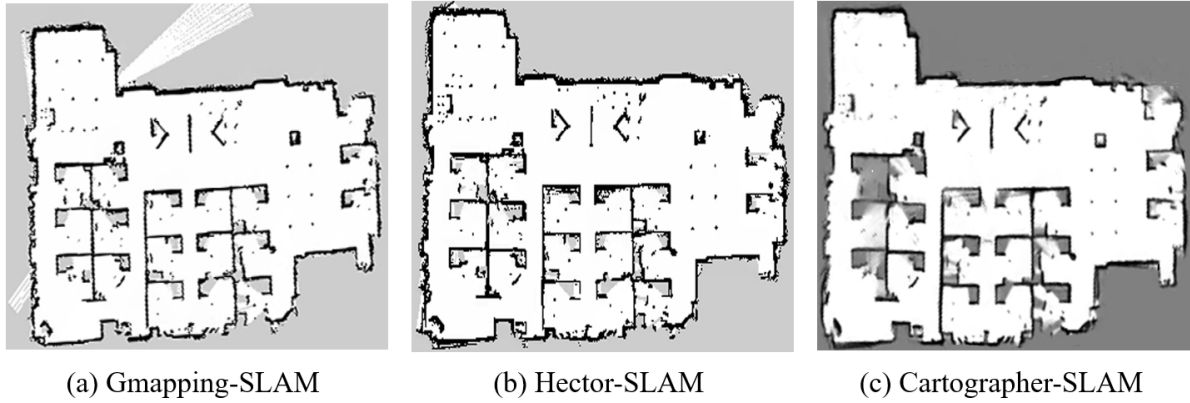


FIGURE 6. Real environment map constructed by three algorithms

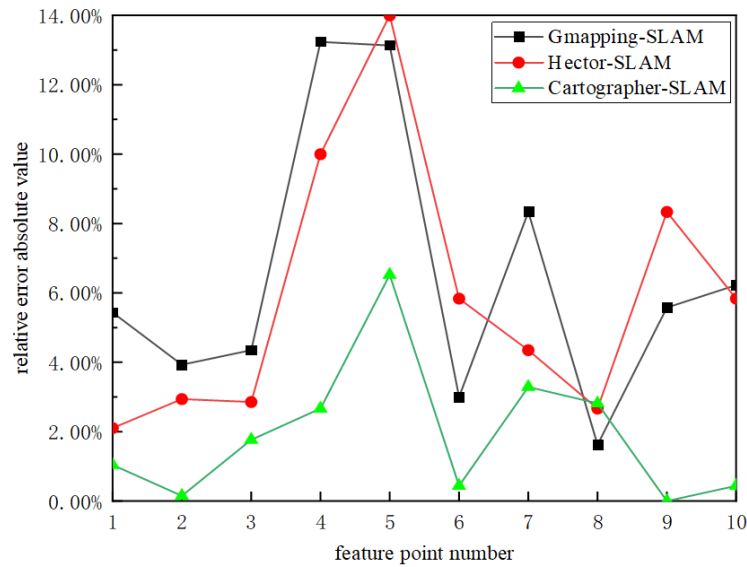


FIGURE 7. Comparison of relative error values of three slam algorithms in real scenarios

of the relative error of the G-mapping SLAM algorithm is 13.24%, the minimum is 1.62%, and the variance is 0.0016. From the perspective of error, the error of the cartographer-slam algorithm is the smallest, and the variance is also the smallest from the perspective of error stability, which shows that the cartographer-slam algorithm has the best stability. The stability of the Hector SLAM algorithm is slightly better than that of the G-mapping SLAM algorithm, and the error is almost the same as that of the G-mapping algorithm. On the whole, the accuracy of the cartographer SLAM algorithm ranks first.

In the process of indoor 2D map construction, according to the experimental conditions and specific environment, the result from the suggested Cartographer SLAM algorithm constructs a two-dimensional map and the perceived indoor environment information completion time. It is seen that the accuracy of the suggested Cartographer mapping algorithm is efficient best compared with the other two algorithms. The CPU utilization rate of the G-mapping algorithm is higher, which also represents the complexity of the G-mapping algorithm. Hector algorithm needs the longest time to complete the map and the lowest efficiency, the CPU utilization is in the middle of the other two algorithms.

TABLE 2. The results of the comparison of the three approaches in real scenarios

Algorithm	Map accuracy	Map completion time (s)	Minimum CPU utilization	Maximum CPU utilization
Gmapping	3	572	35%	50%
Hector	2	913	32%	43%
Cartographer	1	603	33%	41%

5. Conclusions. This study investigated mapping an unfamiliar environment for navigation of mobile robots based on the cartographer SLAM algorithm. The construction of 2D lidar maps in an indoor environment is a challenging task as large map construction, the much error, the high occupation CPU rate, and the increased hardware requirements. Simulation and actual experiment scenarios are used to evaluate the suggested approach. A built-in crawler mobile robot test is mainly equipped with Lidar A1 radar and the Jetson nano main control board with running memory for a real scenario. A robot operating system (ROS) is used to construct a simulation environment for making mainstream map implementation as in an indoor portable machine test. The obtained experimental results of the suggested approach are compared with the other schemes, such as the G-mapping and Hector approaches, from the perspectives of synchronous positioning and mapping accuracy, computational complexity, and mapping efficiency. The results show that the introduced Cartographer SLAM algorithm performs best in an unfamiliar indoor environment. The suggested approach will apply further applications, e.g., the authenticated key agreement protocol [22, 23] and optimizations [24, 25] in future work.

Acknowledgments. This work was partly supported by the Research Foundation of Fujian University of Technology (GY-Z21025) and the VNUHCM-University of Information Technology's Scientific Research Support Fund.

REFERENCES

- [1] Y. -K. Tee and Y. -C. Han, "Lidar-Based 2D SLAM for Mobile Robot in an Indoor Environment: A Review," in *International Conference on Green Energy, Computing and Sustainable Technology (GECOST)*, 2021, pp. 1-7.
- [2] M. Filipenko and I. Afanasyev, "Comparison of various slam systems for mobile robot in an indoor environment," in *International Conference on Intelligent Systems (IS)*, 2018, pp. 400-407.
- [3] C. Debeunne and D. Vivet, "A review of visual-LiDAR fusion based simultaneous localization and mapping," *Sensors*, vol. 20, no. 7, 2068, 2020.
- [4] K. Koide, J. Miura, and E. Menegatti, "A portable three-dimensional LIDAR-based system for long-term and wide-area people behavior measurement," *International Journal of Advanced Robotic Systems*, vol. 16, no. 2, 1729881419841532, 2019.
- [5] T.-K. Dao, J.-S. Pan, T.-S. Pan, and T.-T. Nguyen, "Optimal path planning for motion robots based on bees pollen optimization algorithm," *Journal of Information and Telecommunication*, vol. 1, no. 4, pp. 1-16, 2017.
- [6] A. Yilmaz and H. Temeltas, "Self-adaptive Monte Carlo method for indoor localization of smart AGVs using LIDAR data," *Robotics and Autonomous Systems*, vol. 122, p. 103285, 2019.
- [7] S. Arshad and G.-W. Kim, "Role of deep learning in loop closure detection for visual and lidar slam: A survey," *Sensors*, vol. 21, no. 4, 1243, 2021.
- [8] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with rao-blackwellized particle filters," *IEEE Transactions on Robotics*, vol. 23, no. 1, pp. 34-46, 2007.
- [9] S. Kohlbrecher, O. Von Stryk, J. Meyer, and U. Klingauf, "A flexible and scalable SLAM system with full 3D motion estimation," in *2011 IEEE International Symposium on Safety, Security, and Rescue Robotics*, 2011, pp. 155-160.

- [10] T. Taketomi, H. Uchiyama, and S. Ikeda, "Visual SLAM algorithms: A survey from 2010 to 2016", *IPSN Transactions on Computer Vision and Applications*, vol. 9, no. 1, pp. 1–11, 2017.
- [11] W. Hess, D. Kohler, H. Rapp, and D. Andor, "Real-time loop closure in 2D LIDAR SLAM," in *2016 IEEE international conference on robotics and automation (ICRA)*, 2016, pp. 1271–1278.
- [12] T.-K. Dao, T.-S. Pan, T.-T. Nguyen, and S.-C. Chu, "A compact Artificial bee colony optimization for topology control scheme in wireless sensor networks," *Journal of Information Hiding and Multimedia Signal Processing*, vol. 6, no. 2, pp. 297–310, 2015.
- [13] J.-S. Pan, T.-K. Dao, T.-S. Pan, T.-T. Nguyen, S.-C. Chu, and J. F. Roddick, "An improvement of flower pollination algorithm for node localization optimization in WSN," *Journal of Information Hiding and Multimedia Signal Processing*, vol. 8, no. 2, pp. 486–499, 2017.
- [14] T.-K. Dao, J. Yu, T.-T. Nguyen, and T.-G. Ngo, "A Hybrid Improved MVO and FNN for Identifying Collected Data Failure in Cluster Heads in WSN", *IEEE Access*, vol. 8, pp. 124311-124322, 2020.
- [15] L. Kang, R.-S. Chen, Y.-C. Chen, C.-C. Wang, X. Li, and T.-Y. Wu, "Using Cache Optimization Method to Reduce Network Traffic in Communication Systems Based on Cloud Computing," *IEEE Access*, vol. 7, pp. 124397-124409, 2019.
- [16] F. Zhang et al., "Application of Quantum Genetic Optimization of LVQ Neural Network in Smart City Traffic Network Prediction", *IEEE Access*, vol. 8, pp. 104555–104564, 2020.
- [17] P.-C. Song, S.-C. Chu, J.-S. Pan, and T.-Y. Wu, "An adaptive stochastic central force optimisation algorithm for node localisation in wireless sensor networks," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 39, no. 1–2, pp. 1-19, 2022.
- [18] T.-K. Dao, T.-T. Nguyen, J. S. Pan, Y. Qiao, and Q. Lai, "Identification Failure Data for Cluster Heads Aggregation in WSN Based on Improving Classification of SVM", *IEEE Access*, vol. 8, pp. 61070-61084, 2020.
- [19] T.-T. Nguyen, J.-S. Pan, T.-Y. Wu, T.-K. Dao, and T.-D. Nguyen, "Node coverage optimization strategy based on ions motion optimization," *Journal of Network Intelligence*, vol. 4, no. 1, pp. 1-9, 2019.
- [20] B. Abbyasov, R. Lavrenov, A. Zakiev, K. Yakovlev, M. Svinin, and E. Magid, "Automatic tool for gazebo world construction: from a grayscale image to a 3d solid model", in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2020, pp. 7226–7232.
- [21] R. Fukui, Y. Yamada, K. Mitsudome, K. Sano, and S. Warisawa, HanGrawler: "Large-payload and high-speed ceiling mobile robot using crawler", *IEEE Transactions on Robotics*, vol. 36, no. 4, pp. 1053-1066, 2020.
- [22] T.-Y. Wu and Y.-M. Tseng, "An efficient user authentication and key exchange protocol for mobile client–server environment", *Computer Networks*, vol. 54, no. 9, pp. 1520–1530, 2010.
- [23] J.-N. Chen, Y.-P. Zhou, Z.-J. Huang, T.-Y. Wu, F.-M. Zou, and R. Tso, "An Efficient Aggregate Signature Scheme for Healthcare Wireless Sensor Networks", *Journal of Network Intelligence*, vol. 6, no. 1, pp. 1–15, 2021.
- [24] T.-T. Nguyen, J.-S. Pan, S.-C. Chu, J. F. Roddick, and T.-K. Dao, "Optimization Localization in Wireless Sensor Network Based on Multi-Objective Firefly Algorithm", *Journal of Network Intelligence*, vol. 1, no. 4, pp. 130-138, 2016.
- [25] S.-C. Chu, Z.-G. Du, and J.-S. Pan, "Symbiotic organism search algorithm with multi-group quantum-behavior communication scheme applied in wireless sensor networks", *Applied Sciences*, vol. 10, no. 3, 930, 2020.